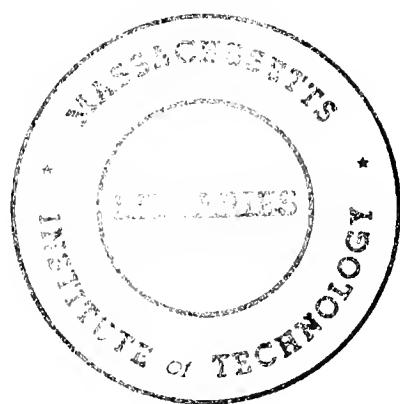


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DEFENSIVE STRATEGY MODELS: APPLICATION AND PREDICTIVE TEST  
by  
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and  
Steven P. Gaskin, Management Decision Systems

February 1983

Draft Working Paper #1404-83, Alfred P. Sloan School of  
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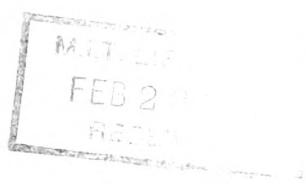
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## ABSTRACT

This paper examines the feasibility, practicality, and predictive ability of the defensive strategy model which was proposed by Hauser and Shugan (1982). We report results in two product categories, each representing over \$100 million in annual sales. We develop "per dollar" perceptual maps and compare the predictive ability of the defensive strategy model to (1) pretest market laboratory measurement models, (2) traditional perceptual mapping procedures, and (3) actual market shares in test market cities. Besides developing an empirical version of the defensive strategy model, our analyses raise a number of behavioral hypotheses worth further investigation.



#### Acknowledgements

We wish to thank Karl Irons, Robert Klein, and Peter Guadagni of Management Decision Systems and Glen Urban and John Little of M.I.T. for their advice, insights, and support throughout this project. The data were supplied by an unnamed sponsor and by Management Decision Systems. The necessary computer support was provided by Management Decision Systems.



## 1. MOTIVATION

In their paper, "Defensive Marketing Strategy", Hauser and Shugan (1982) develop a number of qualitative normative implications on how a firm marketing an established product should defend its profit when facing an attack by a new competitive product. For example, their analyses suggest decreasing budgets for distribution and awareness-advertising while improving the product and repositioning in the direction of the defending product's strength; price should be decreased in unsegmented markets but potentially increased in segmented markets. These implications are derived from a mathematical model of consumer response that assumes heterogeneous consumers maximizing utility in a multi-attributed space.

To obtain quantitative implications, as well as qualitative implications, we must develop an empirical version of the defensive strategy model. We must measure the necessary constructs and estimate the model's parameters. Furthermore, we must have reasonable confidence that a defensive strategy model based on our measures and estimates can adequately predict consumer response.

A key feature of the defensive strategy model is that attributes are measured "per dollar"; for example, laundry detergents might be evaluated with respect to 'efficacy per dollar' and 'mildness per dollar'. Most of the qualitative results do not depend upon this assumption, but quantitative results will require "per dollar" perceptual maps. However, the "per dollar" assumption is untested and, hence, has become quite controversial in marketing science. See discussions in Rao (1982), Ratchford (1982), Sen (1982), and Gavish, Horsky, and Srikanth (1981).

An empirical study of defensive strategy models should examine "per dollar" perceptual maps. Furthermore, such an examination will have



implications beyond defensive marketing strategy. For example, Lane (1980), Lancaster (1979) and Hauser and Simmie (1981) each make the similar assumptions in their models of consumer response.

This paper describes an initial empirical application and test of a defensive strategy model which is based on a "per dollar" perceptual map. We report applications in two (disguised) product categories, each with over \$100 million in annual sales.

## 2. PERSPECTIVE

The primary purpose of this paper is to test the feasibility, practicality, and predictive accuracy of the defensive strategy model. (Following Hauser and Shugan [1981] we call this model 'Defender'.) If Defender is not feasible, if it is onerous to measure and estimate, or if it predicts poorly, then we must reexamine its basic assumptions. If Defender is feasible, reasonably cost effective, and reasonably accurate, then we can proceed to develop managerial recommendations based on the model. In either case, we advance our understanding of how to model consumer response.

(We recognize that Defender is a paramorphic model in the sense that consumers respond as if they followed its assumptions. Other parsimonious models may also be acceptable within the measurement error bounds to which Defender is subject.)

To test Defender, we follow the procedures developed by Hauser and Shugan (1982), making some minor modifications that are justified theoretically prior to parameter estimation. We estimate Defender based on products which are in the market prior to the new entrant. We compare Defender's predictions to (1) predictions of two well-documented marketing science models and (2) measures of market share taken after the new product had entered test market. The former comparison enables us to understand better alternative marketing



science models and assumptions. The latter comparison is an initial test of Defender's external validity.

For model comparison, we chose (1) Silk and Urban's (1978) 'Assessor' model and (2) traditional perceptual mapping/preference regression models as described by Urban and Hauser (1980, chapters 9 and 10).

Assessor has been applied commercially to over 300 products and its predictive accuracy has been scientifically examined by Urban and Katz (1982). Furthermore, it is representative of a class of commercially available 'pretest market models' such as those described in Eskin and Malec (1976), Tauber (1977), and Burger, Lavidge and Gundee (1978). Data collection is clearly feasible for models in this class and predictive accuracy is acceptable to many marketing managers. If Defender can predict as well as Assessor, then we have confidence in its predictive ability.

Analysis with traditional perceptual maps is state-of-the-art methodology as recommended by new product development textbooks (Urban and Hauser, 1980 chapters 9, 10; Pessemier, 1982 chapter 5; Wind, 1982 chapter 4; Choffray and Lilien, 1980 chapter 6) as well as basic marketing textbooks (Kotler, 1983 chapter 2). Traditional maps serve as a standard to which "per dollar" perceptual maps can be compared. Data collection is feasible for traditional maps although their predictive accuracy is not documented as well as for pretest market models.

Our measure of predictive accuracy is based on the share of the new product as measured by SAMI for the test market cities. Although the SAMI measure itself is subject to sampling error and other potentially unobserved errors, we feel it is a reasonable benchmark to which to compare Defender's predictions. Remember that this application of Defender is based on data collected prior to test market and, hence, prior to the SAMI measure.



### 3. DATA

We limit ourselves to the data collected by Assessor supplemented with attribute ratings as collected for traditional perceptual maps. We observe price directly in the marketplace. If we can develop a feasible "per dollar" perceptual map with this standard data, then a careful, evolutionary, Defender-specific improvement of data collection procedures should be feasible, reasonable, and better.

For our initial applications, we chose categories in which variety-seeking, complicated package size issues, and non-monotonic attributes, do not play a major role. We found many categories satisfying these constraints although we recognize that such issues may need to be faced in other categories. Within these constraints, we selected two product categories. Each category is sold through grocery stores and related retail outlets. Because the firms' defensive strategies derive in part from the Assessor and Defender analyses, we have agreed to disguise the data for publication. The disguising procedure and the measured constructs are described below.

Disguising procedure. All comparison statistics such as predictive error are reported without modification. Market share figures are rounded off to the nearest share point. Perceptual dimensions and prices are reported to one significant digit after the decimal point.

For expositional purposes, we have renamed the first product category, "Gypsy Moth Tape", a product used in the forests of New England to combat insect infestation. We have renamed the attribute dimensions, 'Effective (insect) Control', 'Ease of Use', and 'Professional Quality'. These dimensions make sense for Gypsy Moth Tape and capture the flavor of the disguised category's dimensions. We have renamed the new product, "Attack",



and the three dominant defending products, "Pro-strip", "Cata-kill", and "Tree-Guard", respectively. "Store Brand" represents private label and generic products. To the best of our knowledge, these names are fictitious, but bear some relationship to the perceptual dimensions and the disguised category. For the second product category, we have simply numbered the dimensions and labeled the products A, B, and C.

Data collected. The details of Assessor and perceptual mapping data collection are contained in Silk and Urban (1978) and Urban and Hauser (1980, chapters 9 and 10), respectively. For Defender, we use the following data (Sample sizes were 297 and 263, respectively, for the two product categories.).

- (1) Attribute ratings are obtained on fourteen semantic scales for each product in each consumer's evoked set. The evoked set is those products which the consumer has used, has on hand at home, would seriously consider using, or would definitely not use. (These scales are not necessarily ratio scales. See section 6 for further discussion.)
- (2) Attribute ratings, by consumer, for the new brand are obtained after the consumer has used the brand.
- (3) For each consumer, brand last purchased is recorded. And,
- (4) Unit price is observed in the pretest market cities.

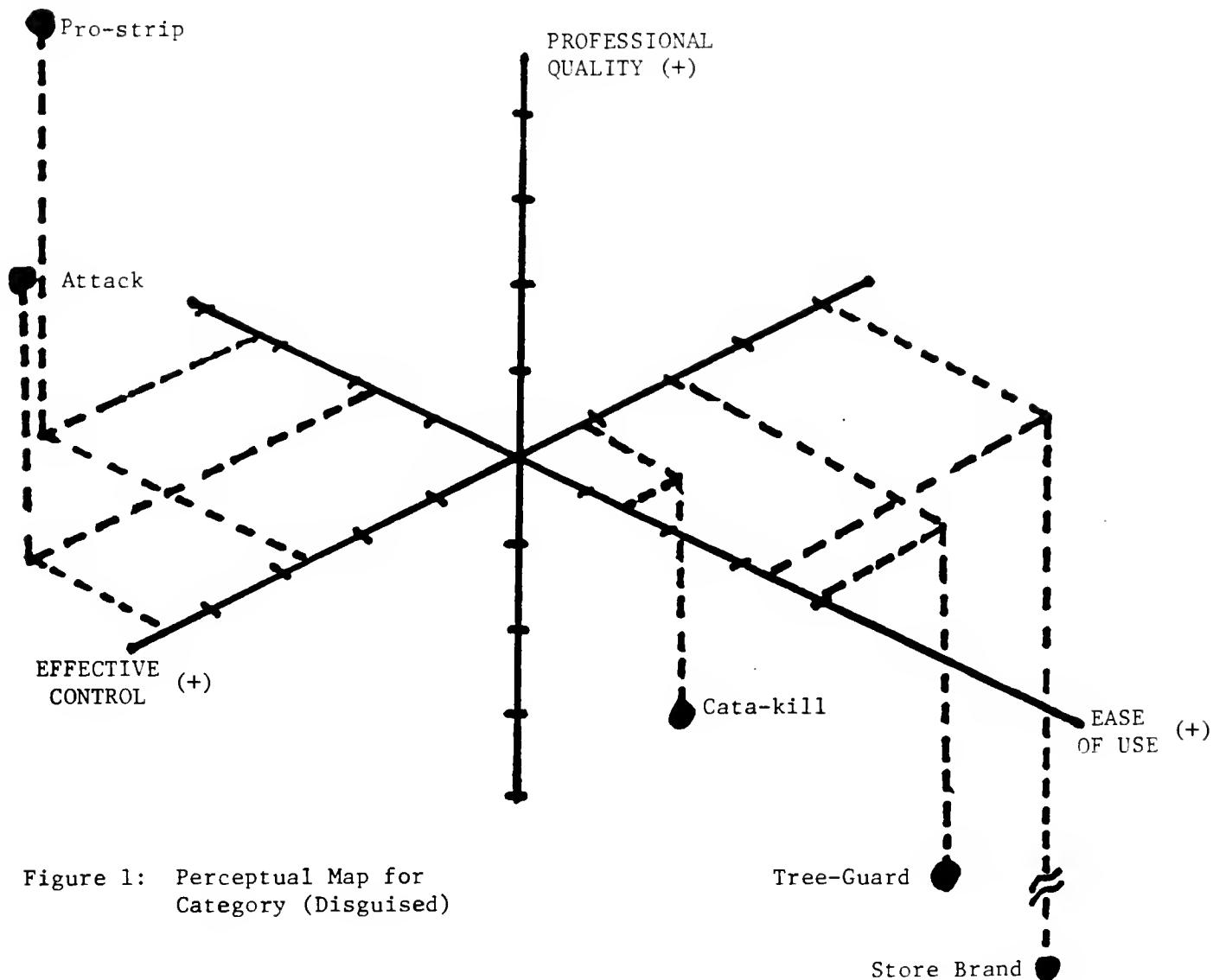
The attribute ratings are factor analyzed as described by Urban and Hauser (1980, chapter 9). In both categories, the best solutions were in three-dimensions explaining 92.5% and 97% of the common variance, respectively. See Table 1 for a disguised version of the factor analysis for "Gypsy Moth Tape". For Defender, we require only the factor scores for each product as averaged across consumers. Figure 1 is the factor analytic perceptual map for "Gypsy Moth Tape".

For comparison to Assessor, we recorded the market shares and awareness and availability forecasts as contained in the final Assessor report provided to the firms. Forecasting procedures are detailed in Silk and Urban (1978).



TABLE 1  
DISGUISED FACTOR ANALYSIS FOR "GYPSY MOTH TAPES"

	<u>Factor Loading</u>
<b>1. Effective Control</b>	
Traps large number of moths	.75
Very sticky	.71
Uses a poison not harmful to children	.67
When used properly, prevents tree damage	.69
<b>2. Ease of Use</b>	
Comes in handy dispenser	.51
Easy to detach single sheets	.71
Does not stick to itself	.59
Sticks to surfaces easily	.71
Comes off easily	.77
<b>3. Professional Quality</b>	
Is not damaged by rain	.52
Lasts a long time	.67
Is thick	.59
Made of fine materials	.71
Made of two sheets glued together	.53





For comparison to perceptual maps, we used preference regression with constant sum paired comparison preference measures for all pairs of brands in each consumer's evoked set. The importance weights were .48, .38, and .14 for 'Effective Control', 'Ease of Use', and 'Professional Quality', respectively. Forecasting procedures are detailed in Urban and Hauser (1980, chapters 10 and 11).

#### 4. REVIEW OF THE 'DEFENDER' CONSUMER MODEL

For ease of exposition, we present the model for two perceptual dimensions and discuss, verbally, how to extend the analyses to the necessary three dimensions. For technical details see Hauser and Shugan (1982).

Evoked set issues. As documented in Silk and Urban (1978) there is considerable variation across individuals in the brands they evoke. If we define an evoked set by the products it contains, then the Defender model first predicts market share within each evoked set and category market share is the weighted sum across evoked sets. (For the four "Gypsy Moth Tapes" there are 15 possible evoked sets.)

Note that because of variation in evoking, a brand may be dominated by another brand yet have non-zero category share. This could result from purchases by consumers who evoke the dominated brand but not the dominating brand. They may not evoke the dominating brand because it is underadvertised and they are not aware of it, or, perhaps, because it is not available where they shop.

Share within evoked sets. Defender assumes (1) that each consumer chooses from his evoked set the product which maximizes utility, (2) that utility is linear in the "per dollar" perceptual dimensions, and (3) that consumers vary in their tastes. Linear utility implies straight-line indifference curves.



For example, suppose that consumer 1 cares only about 'Effective Control'/\$, then his indifference curve will be a vertical line and he will choose Pro-strip as indicated in figure 2a. If consumer 2 cares only about 'Ease of Use'/\$, his indifference curve will be a horizontal line and he will choose Tree-guard as indicated in figure 2b. Finally, if consumer 3 cares equally about 'Effective Control'/\$ and 'Ease of Use'/\$, his indifference curve will make an angle of 45° with the vertical axis and he will choose Cata-kill as indicated in figure 2c.

Clearly, consumers can vary in their tastes, that is, in their willingness to tradeoff 'Ease of Use' for 'Effective Control'.<sup>1</sup> For two perceptual dimensions, we can represent each consumer by the angle,  $\alpha$ , that his indifference curve makes with the vertical axis. See figure 2d.

The market share of a brand, say Cata-kill, will be the percent of consumers whose taste-angles,  $\alpha$ , favor Cata-kill. Thus, if we know the distribution of  $\alpha$  within the population, and if we know the perceptual positions of all brands in the evoked set, we can readily compute Cata-kill's market share. This computation is represented in figure 3. Analytic formulae are derived in Hauser and Shugan (1982).

For three dimensions, indifference curves become planes and we require two angles,  $\alpha$  and  $\beta$ , to represent each consumer. The angle  $\alpha$  still represents tradeoffs among 'Ease of Use' and 'Effective Control', while the angle  $\beta$  represents tradeoffs among 'Professional Quality' and 'Effective Control'. We could also define an angle  $\gamma$  to represent tradeoffs among 'Professional

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<sup>1</sup>Technically  $\alpha$  represents tradeoffs among 'Effective Control' and 'Ease of Use' as well as 'Effective Control'/\$ and 'Ease of Use'/\$, since the "per dollar" scaling cancels out in computing the tradeoffs, that is, in computing  $\tan \alpha$ .



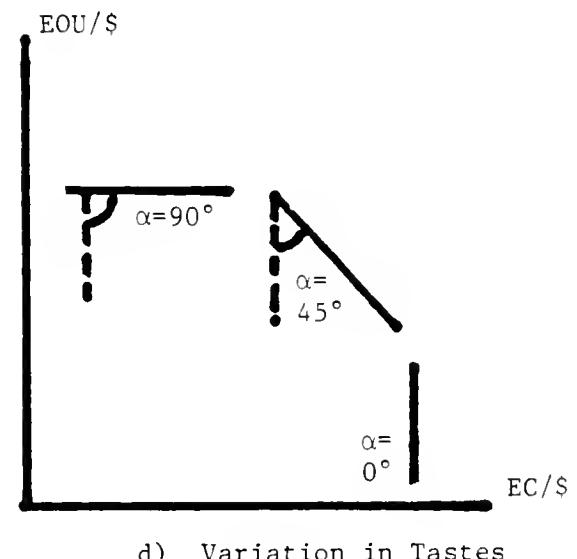
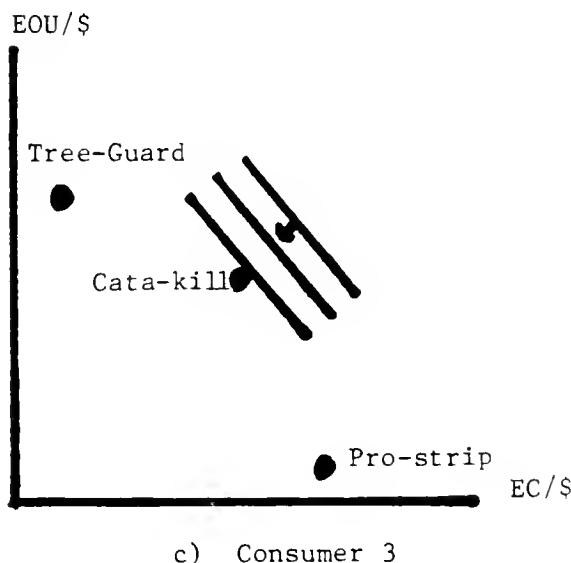
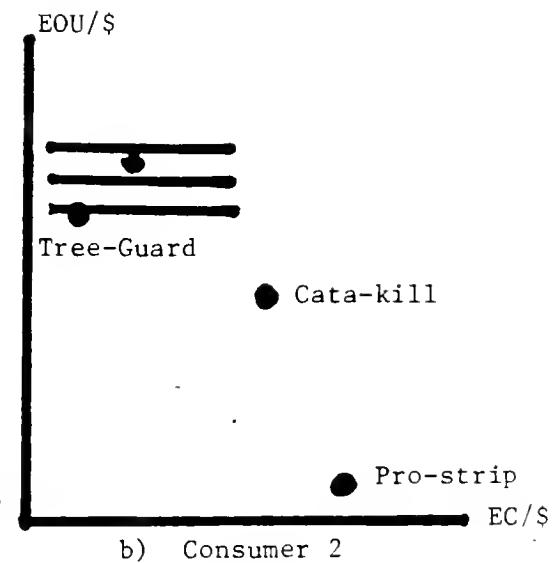
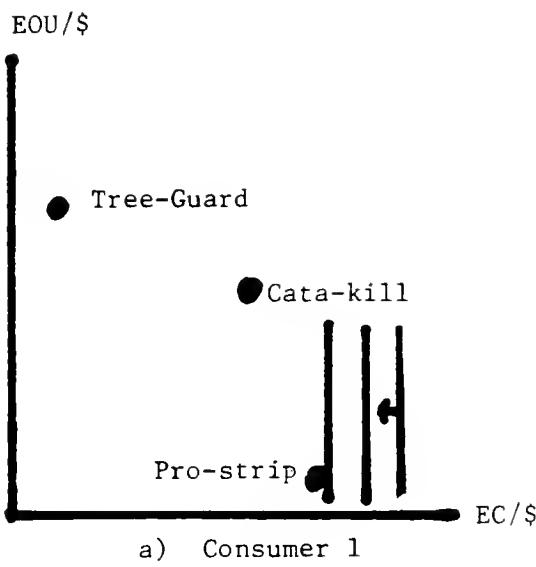


Figure 2: Illustration of How Taste Variation Affects Choice



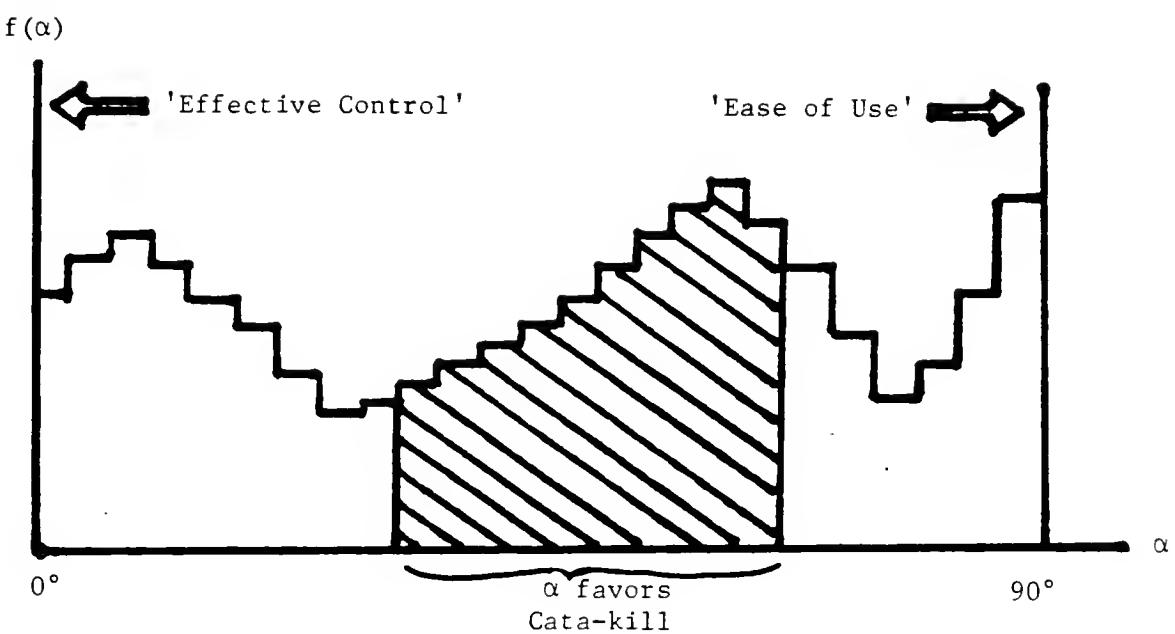


Figure 3: Hypothetical Histogram of Consumer Tastes. (Shaded Area represents market share of Cata-kill.)



Quality' and 'Ease of Use' but  $\gamma$  is uniquely determined by  $\alpha$  and  $\beta$  and, therefore, redundant.<sup>2</sup>

Analytic formulae can be developed for three-dimensions, but the solutions are complex. We overcome this hurdle by dividing the feasible region of the  $\alpha - \beta$  plane into equal areas and, for each area, we compute consumer utility for all brands and assign to that area the brand with the highest utility. To forecast market share within the evoked set, we sum up the areas that a brand, say Cata-kill, captures, weighting each area by the number of consumers with tastes represented by that area. For our applications we use 441 equal areas. (This simple computational procedure is equivalent to numerical Riemann integration of the  $\alpha - \beta$  probability of distribution and, therefore, approximates Hauser and Shugan's integral equations.)

Forecasting of evoking. Hauser and Shugan (1982, p. 42) provide two formulae for forecasting the number of consumers who will be in each evoked set after the new product enters the market. We chose the simpler of the two formulae for our applications. We assume that (1) if a consumer evokes an existing brand before Attack enters the market, he will continue to evoke that brand after Attack is launched, (2) that the probability Attack will be evoked is independent of pre-Attack evoking, and (3) this probability is equal to an advertising index times a distribution index. (One can think of the advertising index as 'awareness' and the distribution index as 'availability', but the model is not limited to these interpretations.)

Thus, to forecast the share of Attack, we place Attack in every evoked set and compute a market share which we call 'unadjusted share'. The actual market share is then given by:

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<sup>2</sup>In particular,  $\tan \gamma = \tan \beta / \tan \alpha$ .



market share = (advertising index)(distribution index)(unadjusted share).

The forecasts for the defending products are obtained in an analogous way.

Controversial measurement issues. Two unresolved measurement issues in the Defender model are the estimation of the consumer taste distribution,  $f(\alpha, \beta)$ , and the use of "per dollar" perceptual maps. Hauser and Shugan (1982) suggest an analytic procedure to estimate  $f(\alpha, \beta)$  from choice data, but this procedure has never before been applied with real data. Section 5 describes the first application.

The more controversial issue is the "per dollar" perceptual map. Factor scores are, at best, interval scaled dimensions. To obtain a "per dollar" perceptual map, we divide the measure of a product's perceptual position by the product's price. However, division assumes that the perceptual dimension is a ratio-scaled measure and that a zero-point, e.g., zero 'effective control', can be identified. The existence of a zero-point does not imply that a product will exist with zero 'effective control', afterall, even a 1972 Cadillac did not get zero 'miles per gallon' yet 'miles per gallon' is a ratio scale. A "per dollar" ratio scale requires that positions of real products can be measured relative to some reference and that a consumer's willingness to pay for an improved brand can be measured relative to that reference point.

However, even if a zero-point is identified, there is no assurance that the resulting "ratio-ized" scale will have the properties we seek. In fact, we may find that no usable zero-point exists. For the purposes of this paper, we treat this issue as an empirical question and attempt to find a usable zero-point. Section 6 addresses this issue empirically and, to some extent, theoretically.

## 5. ESTIMATION OF PREFERENCE DISTRIBUTIONS

Assume for a moment that a zero-point has been identified at 'Effective Control' = -.3, 'Ease of Use' = -.2, and 'Professional Quality' = -.4.



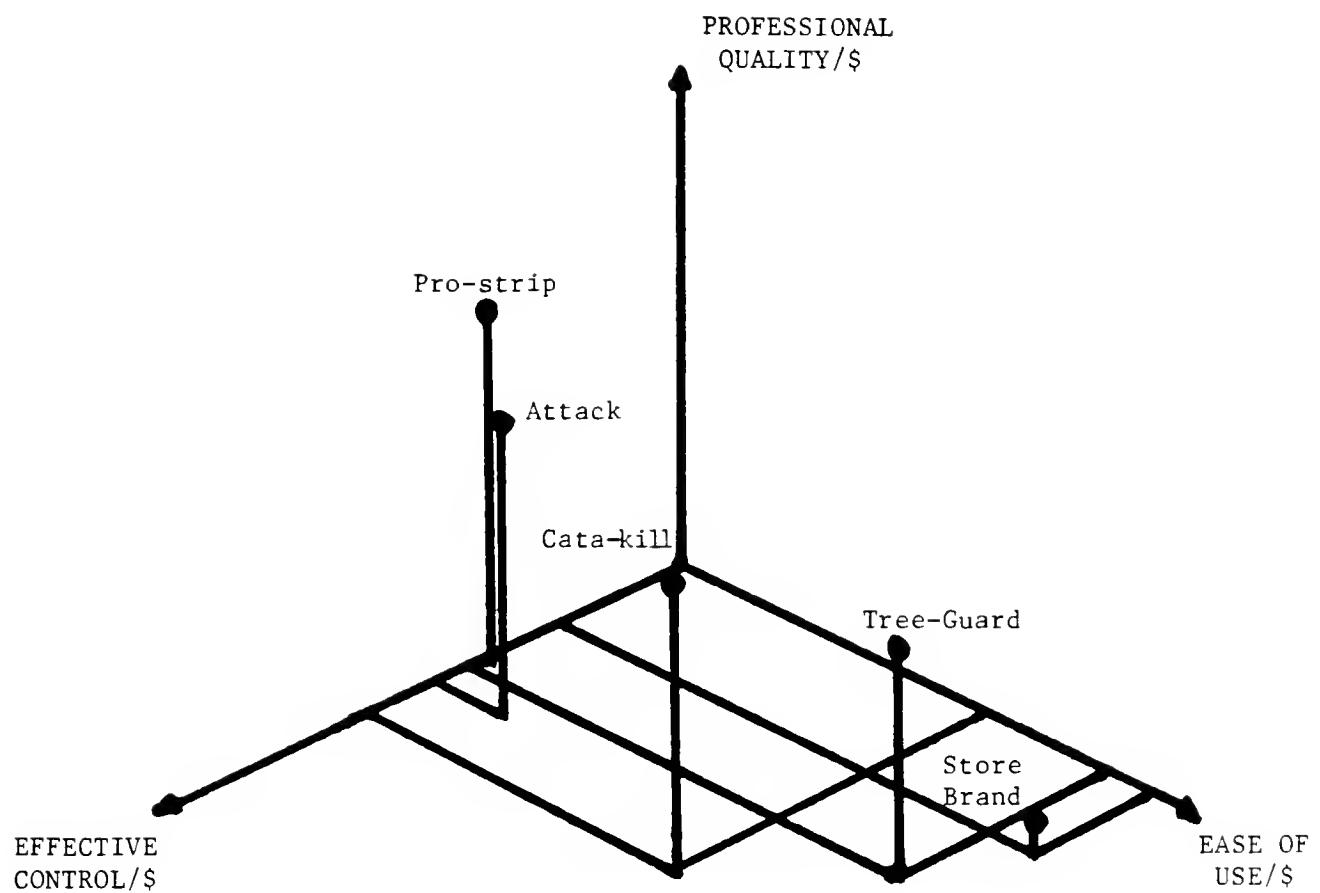


Figure 4: "Per dollar" Perceptual Map (Disguised)



(Details are given in the next section). This zero-point assures that all brands have positive perceptual scores. This map is shown in Figure 4.

If we represent consumer tastes by the angles,  $\alpha$  and  $\beta$ , we must estimate the probability distribution,  $f(\alpha, \beta)$ , that describes the consumer population. Recall that together  $\alpha$  and  $\beta$  represent tradeoffs among the perceptual dimensions as summarized in figure 5. However,  $f(\alpha, \beta)$  can take on many shapes. Figure 6a is a uniform distribution in which all possible taste tradeoffs are equally likely. Figure 6b is a distribution favoring 'Effective Control' over both 'Ease of Use' and 'Professional Quality' while figure 6c favors 'Professional Quality' over 'Effective Control' but assumes all possible tradeoffs among 'Effective Control' and 'Ease of Use' are equally likely. Figure 6d is an example of a more complex multimodal distribution.

Hauser and Shugan (1982) suggest that  $f(\alpha, \beta)$  can be approximated if we adjust piecewise uniform distributions to fit existing market shares within evoked sets and then sum across evoked sets. For example, suppose we examine the evoked set {Pro-strip, Cata-kill}. Among consumers who evoke only these products, Pro-strip has a market share of 48%. However, based on Figure 4, Pro-strip only captures those consumers who place a high weight on 'Professional Quality', i.e.,  $\beta$  close to  $90^\circ$ . Since this region represents only 5.4% of the  $\alpha - \beta$  plane, we adjust this region upward by a factor of 8.9 ( $= .48/.054$ ). This adjustment suggests a 'Professional Quality' segment of the "Gypsy Moth Tape" market as shown in Figure 7.

The Hauser-Shugan procedure is not unreasonable if there are two or more brands in the evoked set. However, suppose that consumers evoke only Pro-strip, which is the best brand on 'Professional Quality' but worst in all else. The Hauser-Shugan procedure would model tastes in this evoked set with a uniform distribution such as shown in Figure 6a. We believe it is more reasonable to assume that such consumers place a high weight on 'Professional



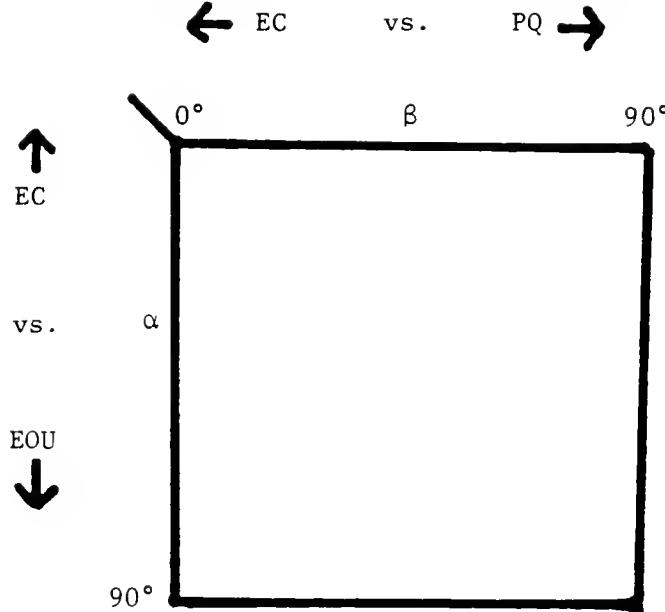
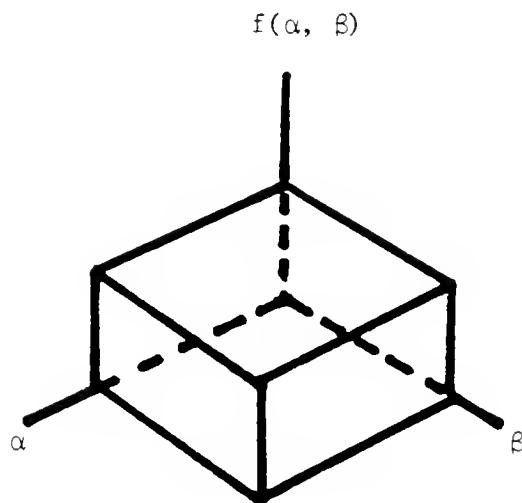
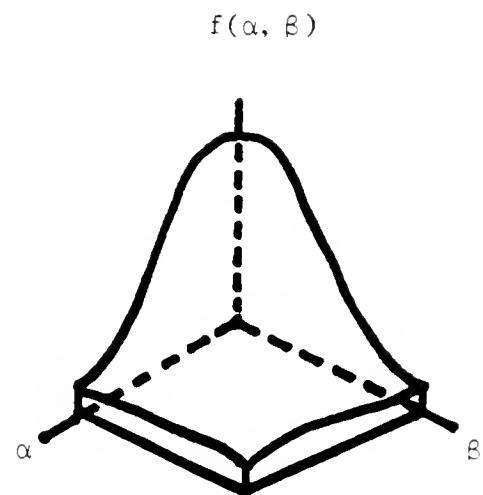


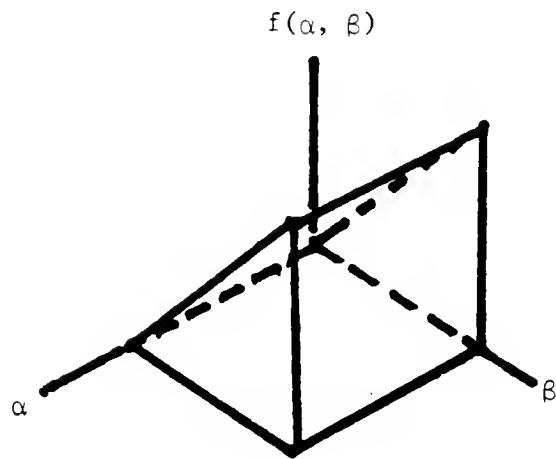
Figure 5: Interpretation of  $\alpha$  and  $\beta$  Taste Parameters



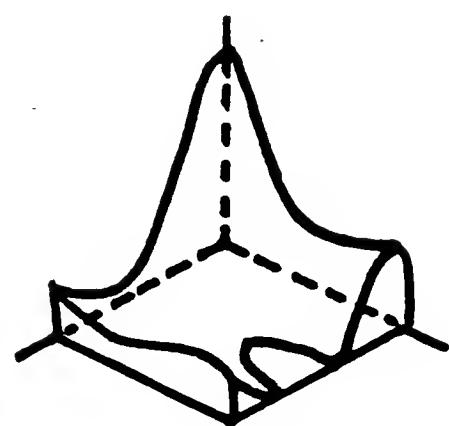
a) Uniform Distribution



b) Distribution Favors 'Effective Control'



c) "Triangle" Distribution



d) Complex Distribution

Figure 6: Some Alternative Taste Distributions



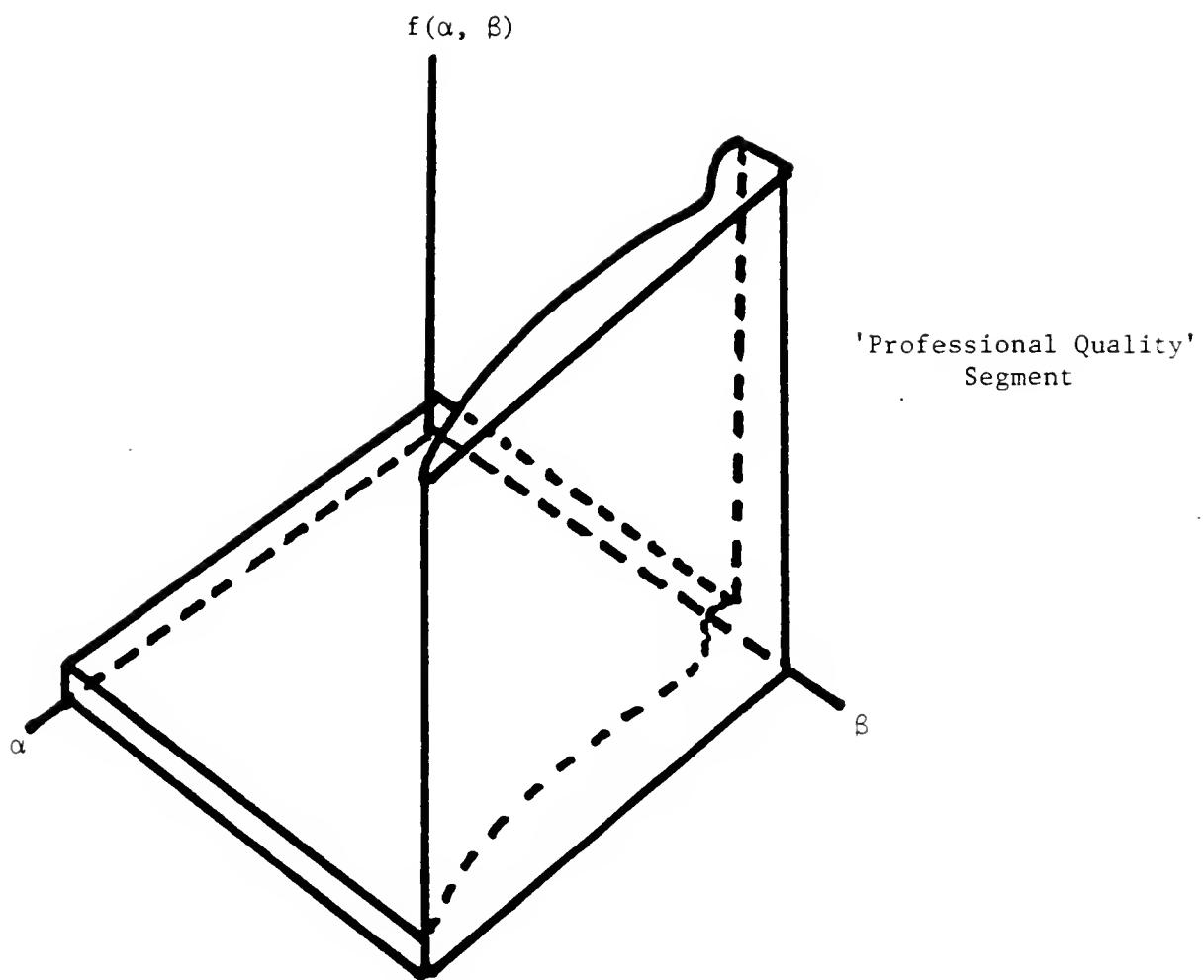


Figure 7: Piecewise Uniform Approximations to Taste Distribution  
(Shown here for a two product evoked set, {Cata-kill, Pro-strip}.)



Quality'. A parsimonious distribution that is consistent with this assumption is the "triangle" distribution in Figure 6c. In our applications, we have modified the procedure accordingly. Whenever the evoked set consists of a single product, and that product is an extreme product such as Pro-strip, we use the appropriate "triangle" distribution. Note that this is a theoretical modification of the procedure made prior to data analysis.

We use the above procedures within each evoke set. We obtain an aggregate  $f(\alpha, \beta)$  by taking a weighted sum across evoked sets. (The weights are proportional to the number of consumers who evoke that set of products.) The final estimate of  $f(\alpha, \beta)$  is shown in figure 8.

To forecast the unadjusted market share of Attack we:

- (1) use the estimate of  $f(\alpha, \beta)$  obtained above for each evoked set,
- (2) use the attribute ratings to place Attack on the traditional perceptual map and use the zero-point and Attack's price to place Attack on the "per dollar" perceptual map,
- (3) identify those areas of the  $\alpha - \beta$  plane that Attack now captures, i.e., those areas for which Attack is the maximum utility brand,
- (4) weight those areas by  $f(\alpha, \beta)$ , and sum across the Attack-captured areas.

Note that  $f(\alpha, \beta)$  is estimated based on existing brands only. We assume that the taste distribution is not affected by the introduction of Attack. This is the same assumption implicit in conjoint analysis (Green and Srinivasan 1978), preference regression (Urban and Hauser, 1980 chapter 10) and logit analysis (McFadden 1980).

Based on this procedure, we forecast the unadjusted share of Attack to be 17%. This is within one standard deviation (based on Urban and Katz 1982) of the Assessor prediction of 19% for Attack. Traditional perceptual mapping analysis predicts a 43% share for Attack which is much greater than the share predicted by either Assessor or Defender. This is not surprising since Attack



is a high-priced premium brand (e.g., over twice as expensive as Cata-kill, Tree Guard or Store Brands) and traditional maps do not adjust for price.<sup>3</sup>

For further comparison, we modified the analysis to include price as an attribute. See Table 2. Although price has a significant coefficient, the coefficient is positive, probably because the higher priced brands, which are also better in the perceptual dimensions, get high market share. Thus, preference regression with price does not do as well as traditional perceptual maps and does much worse than Defender.

The differing performance of traditional perceptual maps and Defender can be explained in part by comparing figure 1 to figures 4 and 8. First, examine figure 1. The preference regression weights imply an ideal vector shaded away from 'ease of use' toward 'effective control' and low on 'professional quality'. Attack does well relative to that ideal vector and, hence, traditional analysis predicts a high share for Attack.

Now examine figures 4 and 8. According to figure 4, Attack is positioned near  $\alpha = 19^\circ$  and  $\beta = 51^\circ$  and Pro-strip near  $\alpha = 5^\circ$  and  $\beta = 64^\circ$ . According to figure 8, Attack captures part of the central portion of the  $\alpha - \beta$  plane, but not the 'professional quality' segment for which Pro-strip is still the best product. However, Attack does take many consumers from Pro-strip in the central area of the  $\alpha - \beta$  plane. Thus, Defender predicts that Pro-strip will hold the 'professional quality' segment while losing its other consumers and that Attack will get 17% of the more central portion of the  $\alpha - \beta$  plane.

Table 2 also compares the post-Attack predictions for all brands in the

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<sup>3</sup>Setting the price of store brand equal to 1.0, the relative prices of Attack, Pro-strip, Cata-kill, and Tree Guard are approximately, 2.9, 2.9, 1.3, and 1.2, respectively.



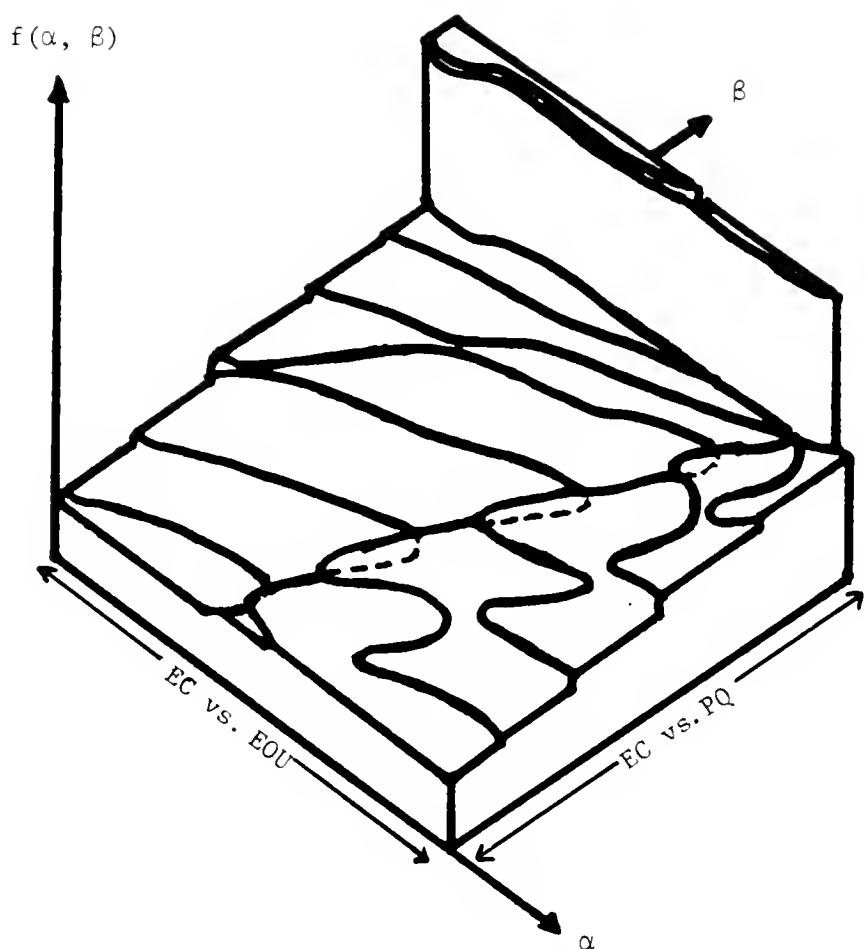


Figure 8: Consumer Taste Distribution,  $f(\alpha, \beta)$ , Representing Tradeoffs Among the Attributes



category. Comparing Defender and Assessor predictions, we see that Defender predicts a greater draw from Pro-strip than does Assessor. This makes intuitive sense by the arguments above since Attack is positioned to draw 'professional quality' consumers who want a product that is easier to use and more effective. Pro-strip previously had a near-monopoly on 'professional quality'. In test market, Attack did indeed draw more heavily from Pro-strip.

At this point the reader may wonder why Defender should be developed if pretest market models (e.g., Assessor) already fulfill the predictive function. First, the Defender prediction requires only that we measure the new product's perceptual position and observe its price. Defender does not require the extensive laboratory measures that are required by pretest market models. Second, and more importantly, the goal of our predictive test is not to establish a better forecasting model, but to investigate the reasonableness of the Defender model. If the Defender model can predict well, then we have more confidence in the qualitative and quantitative defensive marketing strategy implications that are based on the model. Finally, the issue of "per dollar" perceptual maps is scientifically interesting independent of normative implications.

#### 6. RATIO SCALING of "PER DOLLAR" PERCEPTUAL MAPS

The estimates of the preference distribution,  $f(\alpha, \beta)$ , and the predictive accuracy of Defender will vary depending upon the reference zero-point chosen. This section examines the sensitivity of these estimates and predictions as the zero-point is varied. We also examine the sensitivity of the predictions to the choice of the preference distribution.

Feasible region. In order to ensure that all products in the "per dollar" perceptual map have positive scores on each dimension, we must choose a zero-point which is below the minimum value among brands along each dimension



TABLE 2  
PREDICTED UNADJUSTED MARKET SHARES (Disguised Product Names)

	<u>Attack</u>	<u>Pro-strip</u>	<u>Cata-kill</u>	<u>Tree Guard</u>	<u>Store Brand</u>
Pre-Attack	—	.41	.24	.24	.12
Assessor	.19	.37	.18	.18	.08
Trad. Percept. Maps	.43	.26	.13	.14	.05
(with price)	.55	.29	.05	.09	.02
<u>Defender*</u>	.17	.30	.23	.21	.09

\*Zero-point = (-.3, -.2, -.4)



of the traditional perceptual map. For "Gypsy Moth Tape", these minimum values are (-.21, -.17, -.38), respectively, for 'Effective Control', 'Ease of Use', and 'Professional Quality'. The zero-point selected for the analyses in section 5 was chosen to be within the feasible region, but not right on the border of the feasible region. We simply rounded downward to one significant digit. These decisions were made prior to the predictive test.

Sensitivity. We were somewhat surprised that an arbitrarily chosen zero-point did as well as it did. Afterall, it is not guaranteed that a zero-point will exist for which  $f(\alpha, \beta)$  can be chosen to fit market shares of existing brands within evoked sets. Predictive ability is certainly not guaranteed.

We systematically varied the zero-point, re-estimated  $f(\alpha, \beta)$  for each zero-point, and re-predicted Attack's market share. The results are summarized in Table 3. Table 3 indicates that predictions vary, but not dramatically as we vary the zero-point within the feasible region. (Predictions vary from 19% to 13% for the feasible zero-points in Table 3). Interestingly, had we chosen the point (-.21, -.17, -.38), which is the maximum allowable point in the feasible region, we would have predicted 19.5% which is even better than our a priori conservative selection.

Thus it appears that, at least for this one product category, choosing zero-point reasonably close to the boundary of the feasible region allows us to (1) fit the market response to existing brands, and (2) predict the market share of the new brand reasonably well. Furthermore, predictions are reasonably insensitive to the choice of the zero-point as long as it is close to the boundary of the feasible region. We turn now to a brief discussion of possible theoretical explanations for this empirical phenomenon.

Anchoring effect. For "Gypsy Moth Tape" Defender predicts best if we choose the zero-point to be near the maximum allowable point in the feasible



TABLE 3  
SENSITIVITY TO ZERO POINT  
(Predicted Share of 'Attack' as a Function of the Zero-point)

$Z_o = -.3$	$X_o = -.4$	$X_o = -.3$	$X_o = -.2$	$X_o = -.1$
$Y_o = -.1$	.19	.21	.27	.35
$Y_o = -.2$	.18	.20	.25	.31
$Y_o = -.3$	.17	.19	.23	.28
$Y_o = -.4$	.17	.18	.22	.27

$Z_o = -.4$	$X_o = -.4$	$X_o = -.3$	$X_o = -.2$	$X_o = -.1$
$Y_o = -.1$	.15	.18	.20	.28
$Y_o = -.2$	.15	.17	.19	.26
$Y_o = -.3$	.15	.16	.18	.24
$Y_o = -.4$	.14	.16	.18	.23

$Z_o = -.5$	$X_o = -.4$	$X_o = -.3$	$X_o = -.2$	$X_o = -.1$
$Y_o = -.1$	.13	.15	.18	.31
$Y_o = -.2$	.13	.15	.17	.30
$Y_o = -.3$	.13	.14	.16	.29
$Y_o = -.4$	.13	.14	.16	.28

----- indicates approximately the feasible region

$X_o$  = zero-point for 'effective control'

$Y_o$  = zero-point for 'ease of use'

$Z_o$  = zero-point for 'professional quality'



region. At this point, we do not know whether this phenomena is specific to the product category or whether it is a generalizable behavioral phenomenon.

If it is a generalizable phenomenon, then it raises an interesting set of strategies in which a firm can launch a "decoy" brand to shift the zero-point and perhaps increase the share of another of the firm's product. Such decoying phenomena have been established experimentally in marketing science. For example, see Huber, Payne, and Puto (1982). In fact, Huber, Payne, and Puto suggest that the (dominated) decoy brand anchors perceptual dimensions and that other brands are then measured relative to the decoy.

The Huber-Payne-Puto anchoring effect explains the predictive ability of the maximum feasible zero-point by suggesting that consumers evaluate products relative to the worst (evoked) product along each dimension. Such an anchoring effect is also consistent with the framing theories of Tversky and Kahneman (1978).

If our results generalize to other product categories, then such generalizations would suggest further investigation of the anchoring effect. We leave this opportunity to future research.

Uniform distribution. The Defender model requires us to estimate a taste distribution,  $f(\alpha, \beta)$ . We wondered how sensitive predictive results were to variations in this taste distribution. For example, how badly would predictions deteriorate if we used a uniform distribution (as in Figure 6a) rather than the appropriate  $f(\alpha, \beta)$ ?

First, we tried a uniform distribution without any model adjustments and found that we could not even fit existing shares. Reviewing the literature, we recognized that traditional models which assume taste distributions all require "brand specific constants", that is, constants that are added to the utility of each existing product. For example, both logit analysis, which assumes Weibull taste distributions, and preference regression, which assumes



Gaussian taste distributions, require brand specific constants for consistent estimators. See discussion in Coslett (1982). For a related viewpoint, see Srinivasan (1980). Thus, for a uniform taste distribution, we felt it was appropriate to include brand specific constants in the Defender model.

Analogous to logit and preference regression procedures, we selected brand specific constants for each of the existing brands by fitting the Defender model to existing market shares. It was feasible to find brand specific constants. However, to predict, we need to forecast the brand specific constant for 'Attack'.<sup>4</sup> Since this is equivalent to forecasting market share, we conclude that, at least for "Gypsy Moth Tape", the taste distribution contains important information about the product category and is, therefore, necessary to the model. A uniform distribution is not sufficient.

The empirical importance of the taste distribution,  $f(\alpha, \beta)$  is satisfying since Hauser and Shugan (1982) allocate considerable theoretical effort to investigating the impact of the taste distribution. For example, a uniform distribution implies that the optimal defensive price response is to decrease price, but a multi-model taste distribution may imply a price increase.

Stability. As a final test, we assumed a uniform distribution, fit brand specific constants, and, with those constants, systematically varied the zero-point. Figure 9 is a contour map in which the sum of squared errors (SSE) of true market share versus predicted market share is plotted as a function of the zero-point. (Figure 9 is for  $Z_0 = -.4$ , we obtain similar

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<sup>4</sup>The problem of estimating brand specific constants for new brands is a recurring problem in logit analysis. The problem Defender faces when  $f(\alpha, \beta)$  is limited to a uniform distribution is not different qualitatively from that faced in logit analysis.



plots as we vary  $Z_0$ .) As figure 9 indicates, model fit is unimodal in the sense that it systematically degrades as we move away from the chosen zero-point. We obtained similar stability for a variety of chosen zero-points with and without 'Attack' in the market.

The continued stability of the fitting algorithm under a variety of conditions, even for a mis-specified taste distribution, is further evidence to suggest that the choice of a zero-point is a "well-behaved" optimization problem.

Summary. Based on the above sensitivity analyses, for the product category under test, we conclude that:

- (1) With the appropriate taste distribution, Defender predicts well for zero-points close to the maximum feasible values.
- (2) Predictions are reasonably insensitive to the choice of a zero-point if it is close to the maximum feasible value.
- (3) Predictions are sensitive to the choice of the taste distribution.

We return to these conclusions and to the anchoring hypothesis in section 8 when we test Defender in a second product category.

## 7. EXTERNAL VALIDITY

We are encouraged by the ability of Defender to match the predictive ability of Assessor for unadjusted share. However, actual share is based on adjustments due to awareness and availability. For our purposes, we use the awareness and availability forecasts contained in the Assessor report. For Attack, these estimates were .7 and .6, respectively, yielding an adjusted share forecast of 7.1 percent.

Deciding what to use as "actual" share is not easy. The raw data used in Defender (and Assessor) is "last brand purchased". The "actual" shares available to us from test market are SAMI measures of volume share and of



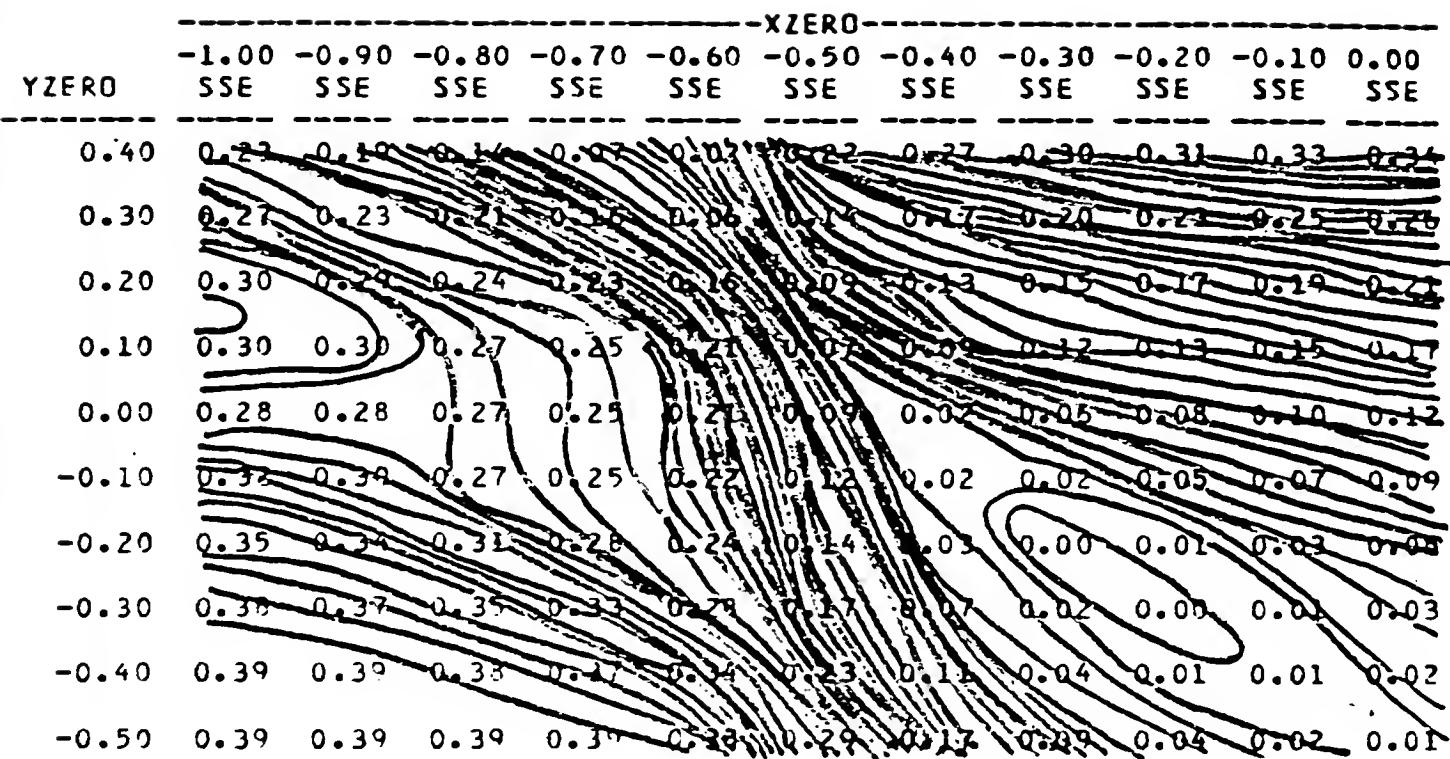


Figure 9: Contour Plot of Sum of Square Error (SSE) for Uniform Distribution

$(X_0 = \text{zero-point for 'Effective Control'}, Y_0 = \text{zero-point for 'Ease of Use'}, \text{for this plot } Z_0 = \text{zero-point for 'Professional Quality'} = -.4)$ .



dollar share. At first, one might expect the appropriate measure is volume share, but in this category Attack and Pro-strip tend to be reused whereas store brand requires more product per use. Thus, volume share will be less than last brand purchased for Attack and Pro-strip and more for store brand. Dollar volume corrects for some of this measurement bias since the reusable brands cost more and store brands cost less, but dollar volume is still an imperfect measure.

Furthermore, SAMI measures factory shipments which is primarily for large grocery stores, yet "Gypsy Moth Tape" is also sold in drug stores and mass merchandisers. This introduces unknown random error in the SAMI measures.

Despite the drawbacks in using SAMI data as an external validity measure, we feel the reader would find the comparisons interesting. Table 4 reports both the volume and dollar SAMI shares for the two test market cities one year after the initial data collection. For ease of comparison and confidentiality we have averaged across the two cities.

Examining Table 4, we see that the SAMI shares are .07 for volume share and .08 for dollar share. Thus, the corresponding "last brand purchased" share would be in the range of .07 to .08. Both Defender and Assessor forecast shares in this range whereas traditional perceptual maps are off by over a factor of 2. We note that in other product categories, predictions may not be as close as the predictions in Table 4. Urban and Katz (1982) report a standard deviation in predictive errors of about 2.0 percentage points. We expect Defender to be in that range.

In summary, despite potential differences in measures, Defender's prediction comes quite close to the SAMI share.

## 8. TESTS IN A SECOND PRODUCT CATEGORY

Defender was successful for "Gypsy Moth Tape", but we must examine whether



TABLE 4  
COMPARISON OF FORECAST MARKET SHARES  
TO TEST MARKET RESULTS

	<u>Share</u>
<b>Predictions</b>	
Assessor	.08
Traditional Perceptual Maps	.18
Defender	.07
<b>Test Market Results*</b>	
SAMI dollar share	.08
SAMI volume share	.07

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\* Test market shares are four-week SAMI shares measured one year after data collection. All shares are rounded to the nearest percentage point for confidentiality. Awareness and availability are assumed to be .7 and .6, respectively.



the results are generalizable. To address this issue, we applied the Defender model to a second product category. This category contained three major brands prior to the launch of a new product, which we call Attack II. (This category also represents over \$100 million in annual sales and is sold through grocery stores and retail outlets.)

Evoking correction. Prior to estimating the Defender model, we identified a data problem in that Brand A dominated Brand B on every dimension, yet consumers, who evoked both Brand A and Brand B, bought B in significant quantities. Any utility maximizing model, whether it be traditional perceptual maps, conjoint analysis, or a "per dollar" perceptual map, would predict almost zero share for Brand B within the category. Careful examination of the category revealed that Brand A had become a generic label for the category much as Kleenex for facial tissues, Xerox for copiers, and Coke for colas. Thus, it is quite reasonable that Brand A was over-evoked. We corrected this "over-evoking" by scaling down reported evoking of Brand A to match observed behavior. Details are contained in Gaskin (1983). While some readers may view this as a "fudge", we point out that (1) such an adjustment would be necessary for any non-stochastic model based on utility maximization, (2) the adjustment was made prior to estimating Defender's parameters and could be automated, and (3) the adjustment used no information about Attack II.

Results. Table 5 reports the predicted share of Attack II for a variety of zero-points within the feasible region. The unadjusted Assessor prediction was 23% market share for Attack II and the maximum feasible zero-point was (-.73, -.21, -.18).

The predictive results in Table 5 are remarkably similar to those in Table 2 for "Gypsy Moth Tapes". Predictions based on the maximum feasible zero-point are within 1.5 standard deviations of the Assessor predictions and



TABLE 5  
PREDICTED SHARE OF ATTACK II (SECOND PRODUCT CATEGORY)  
AS ZERO-POINT VARIES

$Z_0 = -.1$	$X_0 = -.1.0$	$X_0 = -.9$	$X_0 = -.8$	$X_0 = -.7$
$Y_0 = -.2$	.27	.27	.28	.29
$Y_0 = -.3$	.26	.26	.27	.27
$Y_0 = -.4$	.25	.25	.26	.27
$Y_0 = -.5$	.24	.25	.25	.26

$Z_0 = -.2$	$X_0 = -.1.0$	$X_0 = -.9$	$X_0 = -.8$	$X_0 = -.7$
$Y_0 = -.2$	.26	.26	.27	.28
$Y_0 = -.3$	.25	.26	.26	.27
$Y_0 = -.4$	.24	.25	.25	.26
$Y_0 = -.5$	.23	.24	.24	.25

$Z_0 = -.3$	$X_0 = -.1.0$	$X_0 = -.9$	$X_0 = -.8$	$X_0 = -.7$
$Y_0 = -.2$	.24	.25	.26	.27
$Y_0 = -.3$	.23	.24	.25	.25
$Y_0 = -.4$	.22	.23	.23	.24
$Y_0 = -.5$	.21	.22	.22	.23

----- indicates approximately the feasible region



predictions based on zero-points close to the boundary are quite close to the Assessor predictions.

Interestingly, for both Tables 2 and 5, the largest share is predicted for the largest zero-points and predicted share increases monotonically with increases in any dimension of the zero-point. Such a result is not guaranteed by the structure of Defender and, hence, may be either a coincidence or a statement about the type of new product that attacks a mature market. The structural properties of "per dollar" perceptual maps suggest that this phenomenon will occur whenever the attack is a central attack, that is, the new product enters near the center of the perceptual map stressing multiple dimensions. Both Attack and Attack II stress more than one dimension. Since economic theory (e.g., Lane 1980) predicts central attacks for the fourth and fifth products in a category, this phenomena may be worth further investigation.

Tastes and stability. Detailed testing of uniform taste distributions for the second product category replicated the results we obtained for "Gypsy Moth Tapes". A uniform distribution required brand specific constants and plots of SSE were similar to Figure 9.

SAMI data is not yet available to us for this category.

Summary. Based on this second application of the Defender model, we feel that:

- (1) The predictive ability relative to Assessor holds up well. And,
- (2) The anchoring effect, i.e., zero-points close to the boundary of the feasible region, does appear to be a phenomenon worth investigating.<sup>5</sup>

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<sup>5</sup>The anchoring effect is not as strong for the A-B-C category as for "Gypsy Moth Tapes", but it is still there.



The application in this category did require an evoking adjustment, but that adjustment was prior to and independent of the specific estimation procedures of the Defender model.

## 9. BAYESIAN ESTIMATES OF THE NEW PRODUCT'S POSITION

Sections 5 through 9 deal with the estimation and predictive test of the Defender model when the perceptual position of the attacking product is known but its market share is unknown. Hauser and Shugan (1982) also examine the problem from a different perspective and develop procedures to estimate the new product's position from knowledge of its market shares and its effect on the market shares of the defending products.

As detailed in equations 18 through 21 on pages 38-41 of their paper, their Bayesian procedure (1) asks the manager to specify his prior beliefs about the attacking product's position, (2) uses the Defender model to estimate market shares for each potential position, (2) uses the Defender model to estimate market shares for each potential product position, (3) uses sampling theory to estimate the likelihood that the estimated market shares match the observed market shares, and (4) uses the calculated likelihood to update the manager's prior beliefs. Hauser and Shugan (1982) provide a numerical example suggesting that the procedure converges rapidly for four products and two perceptual dimensions.

We implemented their procedure to predict the position of Attack in the "Gypsy Moth Tape" category. (For detailed equations see Hauser and Shugan, 1982; for complete documentation see Gaskin, 1983.)

For a uniform prior, the points with the greatest a posteriori probability of being the true position did contain the true position of Attack and were in the region that Attack had entered, but the points were spread out along a ridge in a diffuse disk. See Figure 10. (We confirmed these results by



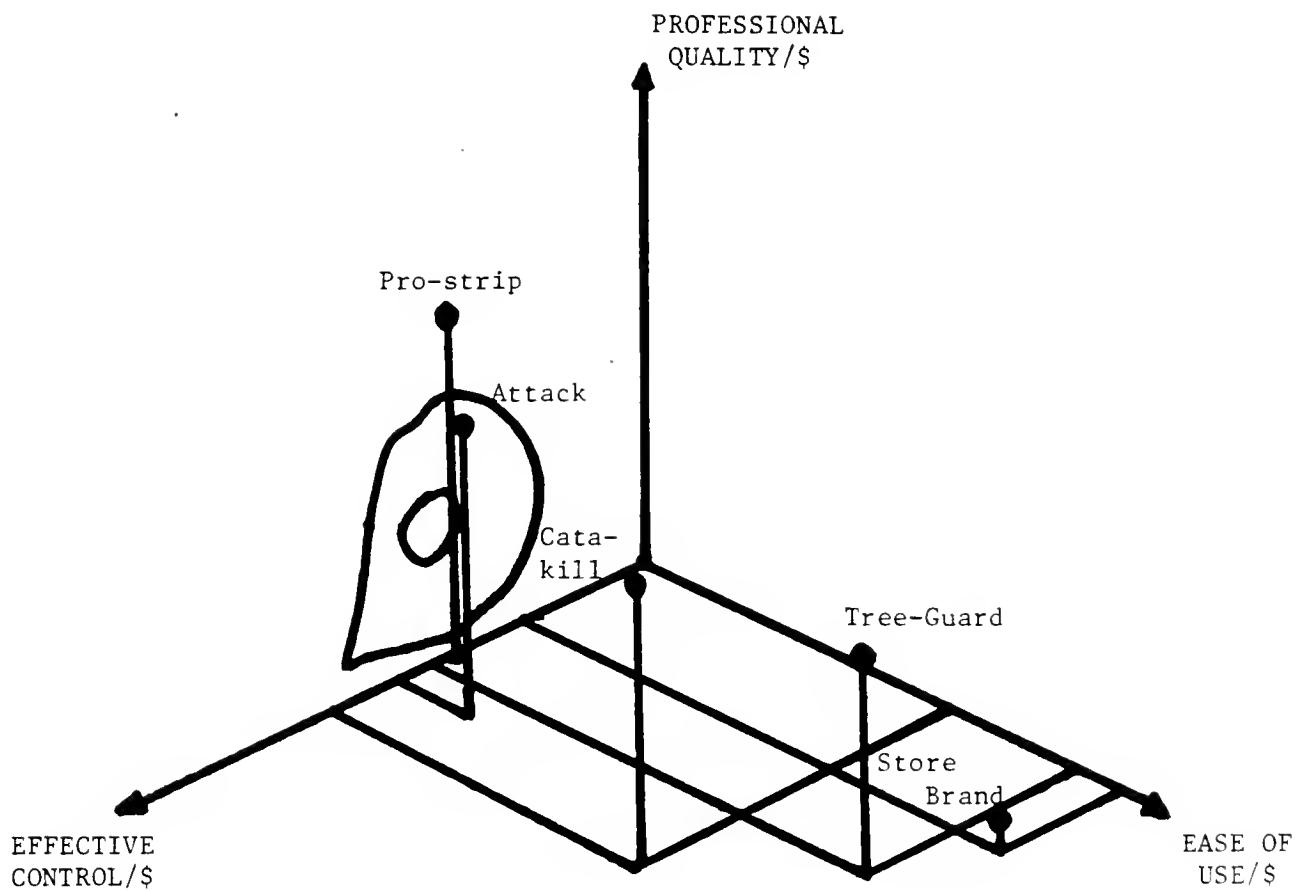


Figure 10: Diffuse Disk Indicating Region of High Posterior Probability



computing SSE's for all points in the disk. As expected, the SSE's were inversely related to the Bayesian posteriors.)

Thus, for the "Gypsy Moth Tape" category, the Bayesian procedure provides reasonable predictions, but predictions that are too diffuse for managerial action. This diffusity is most likely the result of too few products (five) to estimate the position of Attack along three perceptual dimensions. We hypothesize that the procedure would converge more rapidly if there were more products, say six or seven, in the "Gypsy Moth Tape" category.

#### 10. CONCLUSIONS, HYPOTHESES, AND FUTURE DIRECTIONS

This completes our initial test of the Defender model. Based on the results in both categories, we feel that the consumer model predicts as well as existing state-of-the-art models and has good external validity. Because the consumer model is based on empirically observed marketing phenomena, is derived from axiomatic economic theory, predicts as well as highly refined pretest market models, and shows good external validity, we posit that the Defender model is an adequate representation of consumer response. We feel confident in any normative strategies based on the Defender model. (Recall that the Defender model is used for aggregate strategies.)

Furthermore, because we limited ourselves to standard data collection procedures, our results suggest that the Defender model is feasible and well within existing market research data collection budgets.

However, the defensive strategy research stream is far from complete. Our analyses raise as many questions as they answer. The remainder of this section highlights the issues that we feel are most important.

Behavioral hypotheses. Our primary goal was to test the feasibility, practicality, and predictive ability of the defensive strategy model. As is often the case in scientific research based on empirical data, we also



identified serendipitously a number of behavioral, market, and modeling hypotheses. These include the anchoring effect, the evoking adjustment, the multiple dimensional positioning by late entrants, the need for sufficient degrees of freedom in the Bayesian updating, and some observations on heterogeneity. Each phenomena can be explained post hoc by theoretical arguments, but each deserves further testing.

Anchoring. Tests in both product categories suggest that the best zero-points are near the position of the worst product along each dimension. This hypothesis is consistent with experiments and theories in consumer behavior (Huber, Payne, Puto 1982; Tversky and Kahneman 1978) and intuitively appealing. Perhaps it can begin to explain why we are able empirically to "ratio-ize" what theoretically should be an interval scale.

Evoking. In the second product category, a significant fraction of consumers chose a dominated product. We modeled this phenomena as over-evoking of a product that identifies the category. The dominated product was also the first product launched in the category. Thus, the "rewards to first entrant" theories in marketing (Urban 1982) and in economics (Schmalensee 1982) could provide an alternative explanation.

Multiple dimensions. Both Attack and Attack II entered the market with relative strengths on more than one dimension. Since Attack was the fifth major product in its market and Attack II was the fourth major product in its category, these multiple-dimensional attacks are consistent with the economic theories of Lane (1980) which suggest that such late entrants in a category use a central attack.

Bayesian limits. We often think of Bayesian techniques as performing miracles, but our results in section 9 suggest that the Bayesian procedure is limited by the same degrees of freedom constraints that would be faced by a classical maximum likelihood procedure. One needs sufficient products in the



category in order to identify the new product's perceptual position. At least two or three products per dimension should be a minimum constraint.

**Heterogeneity.** Traditional perceptual maps, which use preference regression or logit analysis model perceptions as heterogeneous. Assessor and stochastic preference theory (Bass 1974) model preferences as heterogeneous. Conjoint analysis and Defender model the consumer taste distribution as heterogeneous. All predict well under the right circumstances. Thus, it appears that consumers are indeed heterogeneous, but that the analyst can choose to model this heterogeneity at any stage in the physical characteristics to perceptions to preferences hierarchy. Probably consumers are heterogeneous at each step, but once one step is modeled as heterogeneous, the analyst faces diminishing returns if he tries to model another step as heterogeneous.

Future directions. The most controversial assumption in the Defender model has been the "per dollar" perceptual map. This paper has addressed that issue. The next step is to develop a full normative application including response functions to predict awareness, availability, and perceptual position as a function of dollar spending by the defending firm. In theory, response functions are feasible using a variety of techniques suggested by Little (1975) and others, however, it is a non-trivial task to develop these response functions. Research is underway to develop response functions for "Gypsy Moth Tape", for a major OTC drug category, and for a clearing product category.

Future research includes investigation of the behavioral hypotheses, validation in more product categories, validation of Defender's forecast of price elasticity, further validation of Defender's forecasts of draw from existing brands, and improvements in data collection. We are excited about research on defensive marketing strategy and we hope that our analyses encourage other researchers to share this challenge.



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